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A NEW TECHNIQUE TO ESTIMATE PRECIPITATION USING GOES AND RADAR DATA

by

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ATMOSPHERIC ENVIRONMENT SERVICE

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ABSTRACT

This report presents an investigation to develop a new technique to estimate precipitation using GOES visible and IR data. The use of combined satellite and radar data, wherever available, has also been investigated. The developed methodology is based on a threshold optimization technique combined with a statistical model whose parameters are selected on the basis of a physical/mathematical model. Optimum threshold temperature and brightness are selected on the basis of the least standard prediction error of validation using split sampling technique. The results obtained using the developed technique are also compared with those obtained using some of the existing techniques. The preliminary results indicate that GOES data are useful for estimating areal precipitation.

RÉSUMÉ

Ce rapport présente l'étude de conception d'une nouvelle technique qui permet d'estimer les précipitations d'après les données visibles et IR du GOES. Le cas échéant, on examine aussi l'usage de données satellitaires et radar combinées. Les méthodes ainsi élaborées reposent sur une technique d'optimisation du seuil et un modèle statistique dont les paramètres sont choisis d'après un modèle physique et mathématique. On choisit le seuil optimal de température et de luminance d'après la moindre des erreurs types de prévision en matière de validation, en recourant à la technique de l'échantillonnage fractionné. On compare aussi les résultats fournis par la technique conçue aux résultats obtenus selon les techniques actuelles. D'après les résultats préliminaires, les données GOES sont utiles pour estimer les précipitations surfaciques.

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1. INTRODUCTION

Hydrologic analysis in general and hydrologic rainfall-runoff models in particular are significantly hampered by the lack of accurate precipitation data, particularly in those areas where there is very large spatial variability in precipitation distribution. Conventional gauging of rainfall is rarely capable of responding to spatial and temporal variability in precipitation patterns. Remote sensing measurements, using both radar and multiple spectral scanners on board of satellites hold great promise in providing better information. Geostationary Operational Environmental Satellites offer an excellent and unique source of information on the earth and its related weather systems on a global scale. Geostationary satellites provide imagery on a repetitive basis from the same vantage point at an interval of 30 minutes or less with a remarkable resolution to coverage ratio of the order of $1:10^3$. In spite of the fact that visible and IR sensors do not directly measure rainfall, their high temporal and spatial resolutions have lured researchers over the years to use satellite information for rain estimation. Five geostationary satellites around the earth completely cover the whole globe. The sub-satellite resolution is (0.8 x 0.8) km in the visible (0.55 - 0.77) μm and 3.2 x 6.4 km in the infrared (10.5 - 12.6) μm. The visible channel can be used to deduce information on thickness of the clouds, their geometry and composition. The infrared sensor provides information on temperature and consequently on height of the cloud tops. Since rainfall production is related to all of these parameters, numerous researchers have attempted to estimate rainfall rates using data from geostationary satellites.

The physical basis for the development of various rain estimation techniques is that high brightness implies large cloud thickness, which means greater probability of rain; while low temperature implies high cloud tops which implies large thickness and greater probability of rain (Barrett and Martin, 1981). In the past, most techniques were developed based on only one aspect, i.e. brightness or temperature of the clouds. But both these approaches suffer from their respective inherent drawbacks. For example, the brightness enhancement suffers from signal saturation and dependence on sun angle and viewing geometry. The infared method is compromised by cirrus contamination and resolution (Martin and Scherer, 1973). Martin and Scherer (1973), while reviewing various satellite methods, concluded that better estimates of rainfall would come from combined visible and IR observations than from either used alone. The brightness enhancing or infrared techniques alone may be inadequate to deduce details of convective activity. Similar views were held by others, e.g., Lovejoy and Austin (1979), Bellon et al. (1980), Wu et al. (1985) and Tsonis and Isaac (1985). These observations were further substantiated by a similar type of study by the authors (1987) who concluded that both visible and IR imagery are statistically significant in rain estimates. Techniques developed on the basis of only either one of the sensors may lead to incorrect estimates of precipitation. The present study is intended to elaborate further on this aspect.

The objective approaches to estimate rain may be broadly classified into three areas: threshold, grid cell and cloud model (Negri and Adler, 1987). The first class of techniques employs threshold isotherm or brightness criteria to define clouds. These include Griffith et al. (1978), Woodley et al. (1980) and Negri et al. (1984). The present study is similar to these only to the extent that it defines raining clouds by threshold isotherm and brightness. In this study a threshold optimization technique is combined with a statistical model, whose parameters are selected on the basis of a physical/mathematical model.

2. OBJECTIVES AND SCOPE

The objective of this research is to investigate the possibility of development of a new technique to estimate areal average precipitation from GOES visible and IR data which could be used on an automated operational procedure. The possibility of using combined satellite and radar data, whenever available, is also investigated.

The present study is limited to the area covered by Carp and Exeter radars in southern Ontario. This study is preliminary in nature in view of the limited data available for verification of the developed methodology.

3. DATA

The satellite data processed in this study consist of visible and IR imagery from GOES-E for 27 days in month of April 1985. The data were received at Environment Canada's satellite data laboratory in Downsview, Ontario, and stored on computer compatible tapes (CCT). The intensity range of the visible image is 0-63 and that of IR is 0-255. The IR counts are converted to equivalent black body temperature via standard IR calibration. Each IR count represents a 0.5° change from 338°K to 242°K, and 1.0° change from 242° to 163°K (Corbell et al., 1977). However, in this study both visible and IR intensity range was normalized into 25 values, following the procedure adopted by Lovejoy and Austin (1979).

Radar data were obtained from the 5 cm SCEPTRE radar systems located at Carp (45°18'N, 75°59'W) and Exeter (43°21'N, 81°29'W). The archived volume scans were processed to derive a 1.5 km Constant Altitude Plan Position Indicator (CAPPI) at 10 minute intervals. The radar reflectivities were transformed to 10 minute rain accumulations using the Marshall-Palmer distribution (Battan, 1973). In this study, these were accumulated to produce daily rain values.

The rain gauge data was used as a ground truth. The gauge data used in this study is the average of the daily rain data recorded over 370 climatic stations in the entire area covered by the Carp and Exeter radars. Daily rain data for 27 days in April 1985 (Table 1) was used in the present study.

4. METHODOLOGY

The developed technique is comprised of two major steps.

1. Selection of optimum threshold cloud temperature and brightness.

2. Feasibility of relation between threshold temperature, brightness and precipitation.

As outlined in the Introduction, precipitation can be related to both brightness and temperature. However, all of the clouds are not raining ones. The basic assumption in the development of this technique is that only very bright and cold clouds generate measurable quantities of rain. This can be mathematically, written as,

$$R = f(B_t, T_t) \qquad \ldots (1)$$

where R = rainfall
B_t = threshold brightness of clouds measured as visible values
T_t = threshold temperature of clouds measured as IR values

Therefore, the feasibility of a linear regression between the precipitation, cloud brightness and temperature was investigated. Regressions were developed using data accumulated over the entire area, 362074 square kilometres covered by Carp and Exeter radars. Precipitation data used are the areally weighted average of the daily rain data recorded at 370 rain gauge stations in the entire area covered by both radars. GOES visible and IR data are the sum of the 24 images at 1 hour interval for all pixels within the area covered by the radars. First bivariate regressions were investigated between average daily precipitation and total number of IR pixels above various threshold values using precipitation as the dependent variable and cumulative IR pixels as the independent variable. Bivariate regressions were also attempted using cumulative day-time visible and IR pixels or night-time IR pixels as the independent variable. Afterwards, Trivariate regressions were investigated using both day-time visible and IR pixels and night-time IR pixels as independent variables.

5. OPTIMIZATION OF THRESHOLD TEMPERATURE AND BRIGHTNESS

In order to arrive at the optimum threshold brightness and temperature, regressions were developed between daily average precipitation and the total number of visible and IR pixels above various threshold visible and IR values using precipitation as the dependent variable. The particular threshold, which resulted in the optimum value of correlation coefficient and the least standard error of estimation, is the optimum threshold value of temperature and brightness. In the first place, all available data were used to calibrate the regression models. On the basis of the maximum correlation coefficient and the least standard error of estimation values, optimum results were obtained using visible and IR pixels with intensity levels of

higher than 42 and 181 (-36°C) respectively. Regressions were developed using various threshold values. However, results for only three regressions are given here for illustration purposes. The value of correlation coefficient (R) was 0.8264 using total number of vis & IR pixels with intensity levels of higher than 42 and 177 (-32°C), respectively, as independent variables. The value of correlation coefficient increased to 0.8378 using threshold of 42 and 181 (-36°C) for visible and IR pixels, respectively. The correlation coefficient decreased to 0.8324 using visible and IR threshold of 42 and 185 (-40°C), respectively. Similarly, the value of standard error of estimation was 1.339 mm using visible and IR threshold of 42 and 177, which decreased to 1.299 mm with threshold of 42 and 181, respectively. The value of standard error of estimation increased to 1.318 mm when threshold values of 42 and 185 were used for visible and IR pixels.

Afterwards, validation was done using split-sampling technique. Data for 17 days were included in the calibration sample and the data for remaining 10 days were used for validation purposes. The optimization of threshold temperature and brightness was done by comparing actual gauge observed rainfall values with those estimated by the model and minimizing the standard error between them. The standard error of validation was 58.2% using threshold visible and IR values of 42 and 177, respectively. The standard prediction error decreased to 52, 36% using threshold values of 42 and 181 for visible and IR pixels. The value of standard prediction error increased to 59.4 when visible and IR threshold were 42 and 185, respectively. Thus, the optimum threshold values based on the least value for standard error of validation were consistent with those obtained on the basis of the maximum correlation coefficient and the least standard error of estimation using the whole data set.

In view of the fact that use of visible data limits the applicability of the particular technique on operational basis to only day time, a fair amount of time was spent on attempting bivariate regression using only total IR pixels (comulation of day and night) as the independent variable. However, the results using total IR pixels as independent variable were not so encouraging. For example, the value of correlation coefficient were 0.5366 and 0.4878 using total day and night IR pixels above intensity level of 177 (-32°C) and 185 (-40°C), respectively. The corresponding standard error of estimation values were 1.97 mm and 2.03 mm, respectively, for these threshold values. In these regressions whole data were used for calibration purposes.

6. RESULTS AND DISCUSSION

As discussed in the methodology, regressions were developed between daily precipitation and visible and IR pixels above optimum threshold values. First, bivariate regressions were investigated. Then trivariate regressions were attempted. In these regressions, independent variables are 1) cumulative day-time visible and IR pixels having visible and IR intensity levels of higher than 42 and 181 respectively; 2) cumulative night-time IR pixels having intensity level of greater than 181. The detailed results are shown in Table 2. The calibration results were only slightly better using both day and night-time visible and IR data than night-time IR only.

In order to evaluate the performance of the developed model, validation of the model is essential using independent data sets. This will also circumvent serial correlation, if any, in the data. Since enough data were not available for validation purposes, a split sampling technique was pursued. In the first place, data from 17 randomly selected dates were used in the calibration sample (sample 1) and the remaining 10 dates were used to validate the model. The resulting regression equation is:

$$R = 0.012\ (vis + IR)_D + 0.14\ (IR)_N + 0.365 \qquad \ldots (2)$$

where

R = daily rain gauge data in mm.
$(vis + IR)_D$ = sum of day-time visible and IR pixels above optimum threshold values x 10^{-3}
$(IR)_N$ = sum of night-time IR pixels above optimum threshold values x 10^{-3}

The correlation coefficient (R) equals 0.81, and is significant at 99% confidence level. This equation when used to make predictions for the remaining 10 days, resulted in prediction errors as detailed in Table 3. The standard prediction error of validation was 52% (mean rainfall value being 1.51 mm).

The standard prediction error of validation (SE_v) in percent is defined as:

$$SE_v(\%) = \frac{\left[\dfrac{\sum_i^n [(PR_i) - (OR_i)]^2}{n-1}\right]^{\frac{1}{2}}}{\overline{OR}} \times 100$$

where i = 1, 2, ... n
n = number of data used

and PR and OR represent predicted and gauge observed daily rainfall and $\overline{OR}$ is the mean value of the gauge observed rainfall.

In a second split sampling, another set of 17 dates (sample 2) was used to calibrate the regressions model and the remaining 10 dates were used in the validation sample. The correlation coefficient in this case was 0.88, significant at 99% confidence level. The equation when used to predict daily rain resulted in prediction errors as detailed in Table 4.

In order to investigate the effect of combining radar and satellite data, regressions were also attempted using unadjusted radar rain data as

the third independent variable. Bivariate regressions were also developed using unadjusted radar rain data as the only independent variable. The resulting multivariate regression using both satellite and unadjusted radar data as the independent variables (sample 1) is;

$$R = .005\ (vis + IR)_D + .024(IR)_N + 1.189\ RDR + 0.375 \qquad (3)$$

where RDR = Unadjusted radar rain data in mm.

The correlation coefficient equals 0.97, significant at 99% confidence level. The validation results using this equation are given in Table 7. The prediction errors using bivariate regression equation using unadjusted radar data as the only independent variable are given in Table 5.

The regression equation calibrated on the other data set (sample 2) is;

$$R = 0.009\ (vis + IR)_D + 0.118(IR)_N + 1.051\ RDR + 0.03 \qquad (4)$$

The correlation coefficient is 0.94, significant at 99% confidence level. The validation results using this equation are given in Table 8. The validation results using regression equation using unadjusted radar data as the only dependent variable are given in Table 6.

From Table 2, it is evident that results obtained by multiple linear regressions using day-time visible and IR and night-time IR data are only slightly better than using only night-time IR data. The slight improvement by including day-time data may be attributed to the fact that much of the significant rain fell during the night-time for the period of data processed in this study. Data for the period when significant rainfall was recorded during day and night is required to find out the validity of this factor. Other factors like the effect of solar radiation on day-time data and diurnal variation of temperature in the month of April were also considered, but no sound explanation could be found to substantiate these. At present, no firm and conclusive answer can be given to this unusual behaviour of the day-time data due to limited data available for this study.

Tables 2-8, also indicate that results obtained by using combined satellite and radar data are better than those obtained by using only satellite data, except in the case of one sample when standard error of validation using satellite data was less than that with both satellite and radar data. Better validation results in the case of one set of data may be attributed to the nature of this very sample. However, further validation is required to arrive at any firm conclusion in this regard.

Similarly, the results obtained by using data both from satellite and radar are better than those obtained from radar only. Thus inclusion of the satellite data improves the radar results.

A comparison of the results from this technique was done with those obtained from three of the existing techniques using the same data set. The technique selected for comparison purposes were Negri et al. (1984), RAINSAT developed by Lovejoy and Austin(1979) and Hogg et al. (1986). The estimated rain values employing these techniques were obtained from Hogg et al. (1986). These rain values were regressed against actual gauge observed rain values using rain estimates from those techniques as independent variable and gauge data as the dependent variable. The estimated rain values using these regressions were compared with the corresponding gauge observed rain data to calculate prediction errors for comparison with the developed technique. Detailed results are given in Figures 1 to 5. The developed technique is denoted by technique 1. Figure 1 indicates the correlation coefficient values between rain values estimated using different techniques and the actual gauge observed rain values, when whole data set (27 dates) was used for calibration purposes. Figures 2 and 4 show correlation coefficient between rain estimates obtained from different techniques and actual gauge observed rain values when data for 17 dates (sample 1 and 2) were used in the calibration sample. Figures 3 and 5 represent standard prediction errors when regression equations calibrated on sample 1 and 2, respectively, were used to make estimates for rain for the remaining 10 days. It is indicated from Figures 1 to 5 that results obtained using the developed technique are comparable and in some cases better than those obtained from the above mentioned techniques.

It should be kept in mind that the improved performance of this technique may be partially or even totally explained by the fact that it was developed with the data set which was also used to validate the rainfall estimates.

In this study, all the data have been accumulated over an area of 362074 square kilometres. For practical applications, it would be important to see the effect of subdividing the area. Moreover, the same area has been considered for calibration and validaton of the model. Validation of the model in an area different than the one used for calibration purposes should also be a topic of future stuies.

7. CONCLUSIONS & RECOMMENDATIONS

Conclusions

1. GOES visible and IR data can be used to estimate daily areal average precipitation using the type of models attempted in this paper.

2. Inclusion of radar data in the regression improved rain estimates. Inclusion of satellite data improved the radar too.

3. These results are preliminary in nature. However, the encouraging results obtained warrant further research in this direction.

Recommendations

1. Use of combined satellite and radar data, wherever available, should be investigated in rain estimation.

2. The results of this study should be further checked using additional calibration and validation data.

3. More validation should be carried out in time and space.

4. Adaptability of this technique to smaller areas should also be studied.

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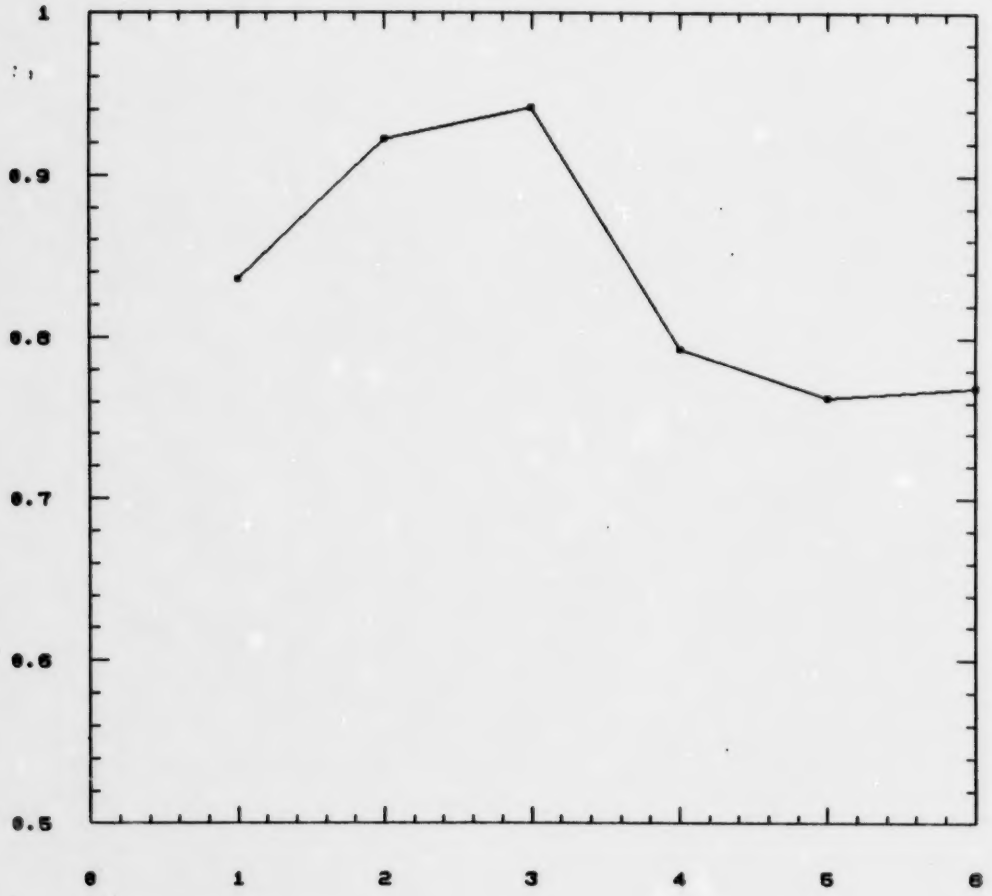
Figure 1. PLOT OF CORRELATION COEFFICIENTS FOR DIFFERENT TECHNIQUES



Technique 1..IR & Vis.

2..Radar (unadjusted)

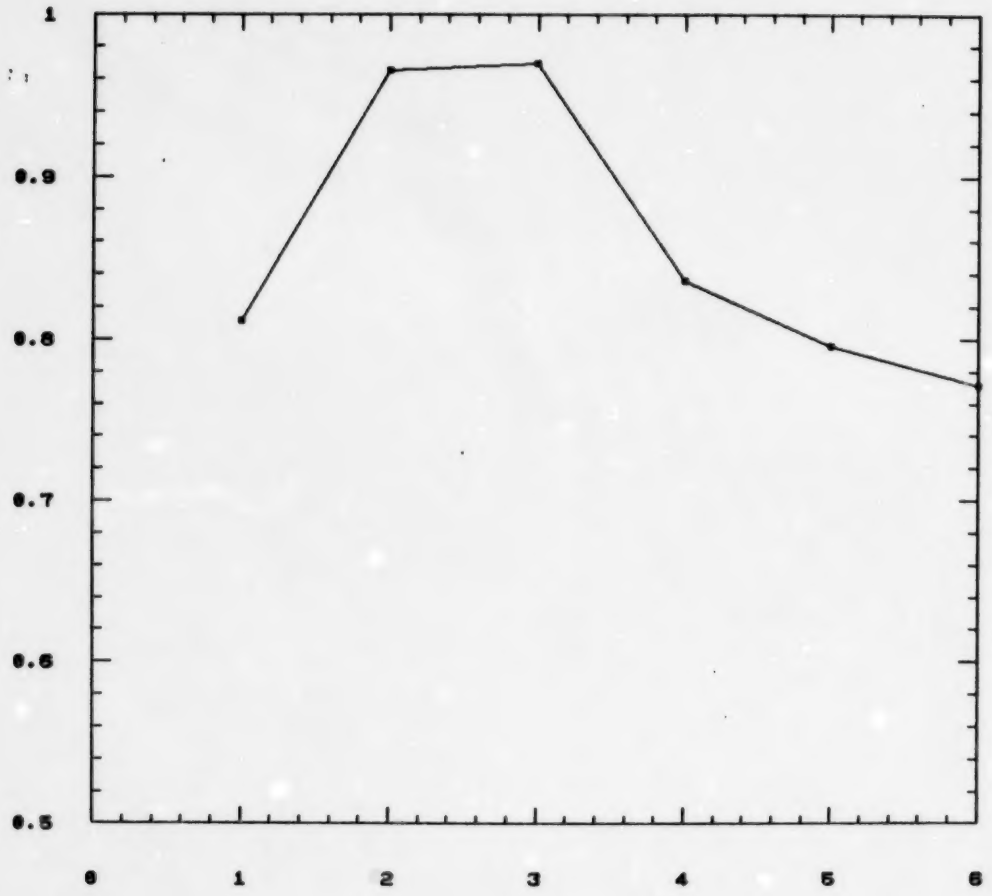
3..IR, Vis. & Radar (Combined)

4..Hogg et al. (1986)

5..Negri et al. (1984)

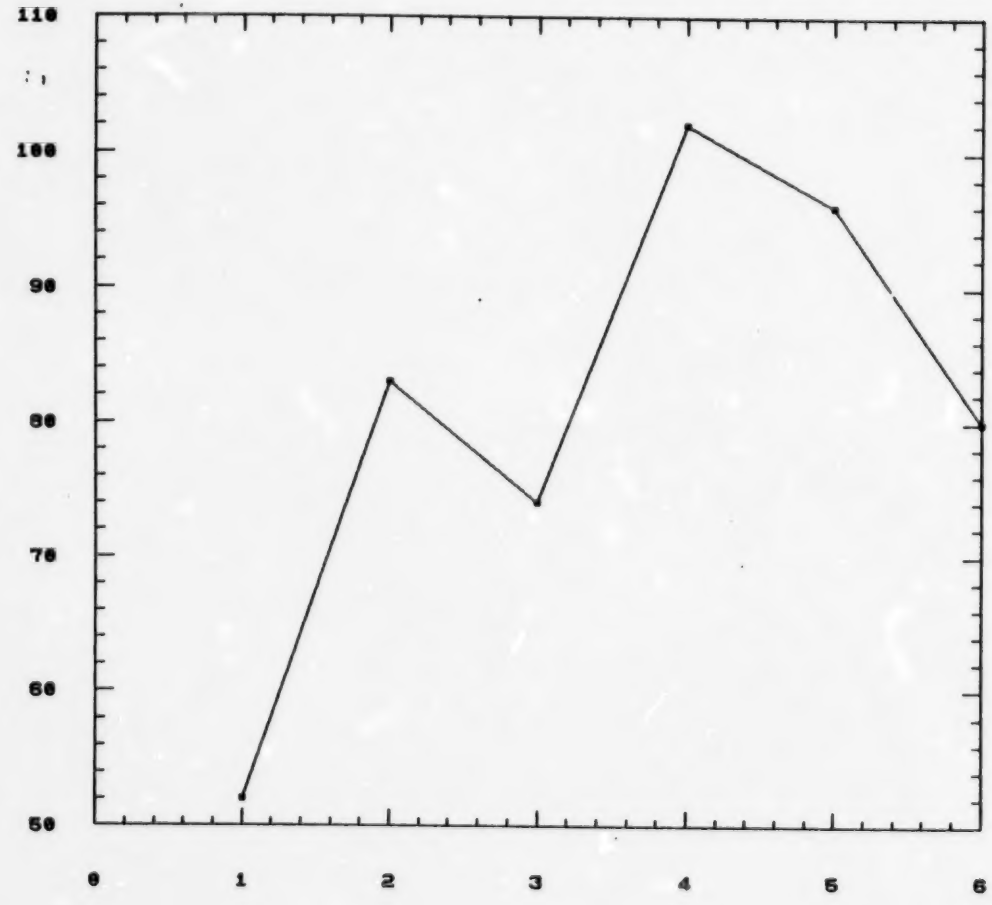
6..Lovejoy and Austin (1979)

Figure 2. PLOT OF CORRELATION COEFFICIENTS FOR DIFFERENT TECHNIQUES (SAMPLE 1)



Technique 1..IR & Vis.
2..Radar (unadjusted)
3..IR, Vis. & Radar (Combined)
4..Hogg et al. (1986)
5..Negri et al. (1984)
6..Lovejoy and Austin (1979)

Figure 3. PLOT OF VALIDATION ERRORS FOR DIFFERENT TECHNIQUES (SAMPLE 1)



Technique 1..IR & Vis.

2..Radar (unadjusted)

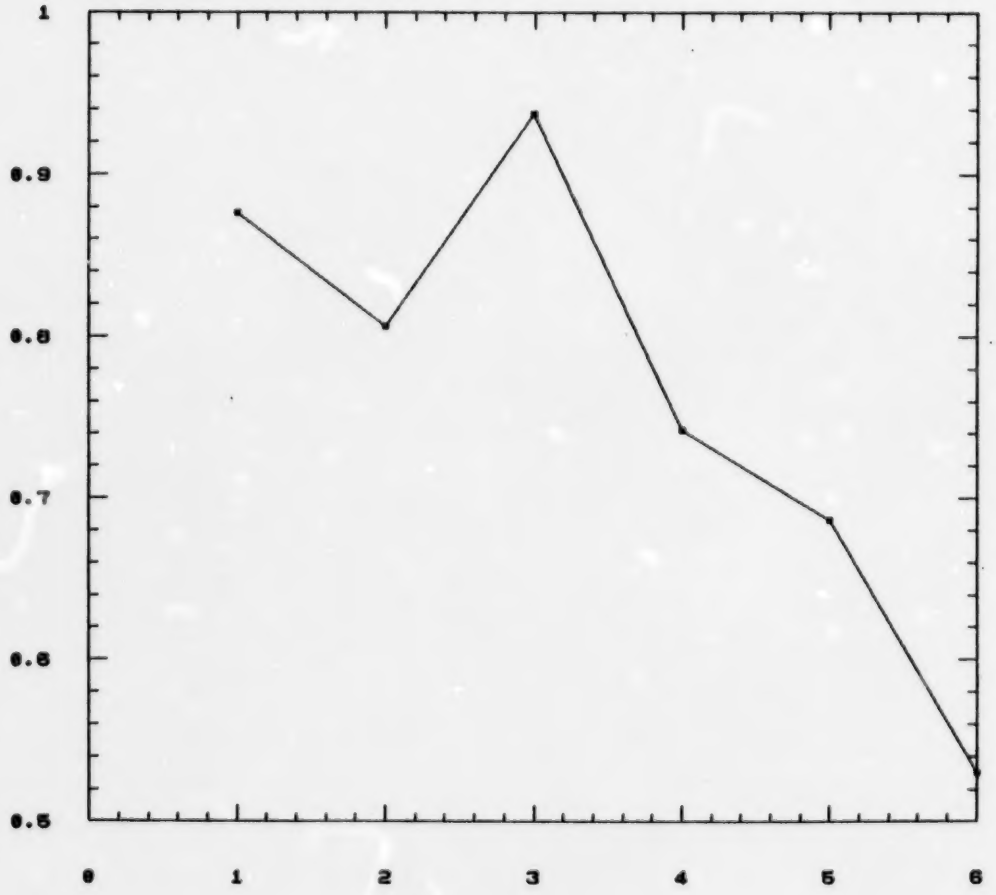
3..IR, Vis. & Radar (Combined)

4..Hogg et al. (1986)

5..Negri et al. (1984)

6..Lovejoy and Austin (1979)

Figure 4. PLOT OF CORRELATION COEFFICIENTS FOR DIFFERENT TECHNIQUES (SAMPLE 2)



Technique 1..IR & Vis.

2..Radar (unadjusted)

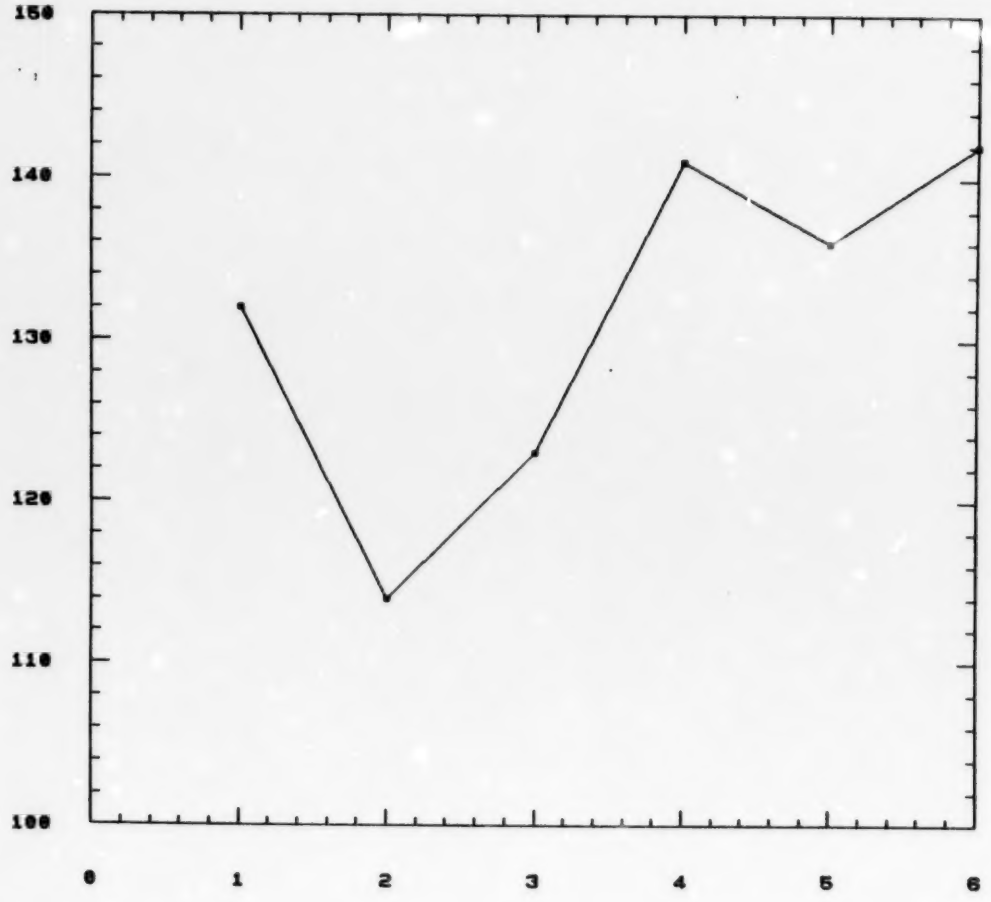
3..IR, Vis. & Radar (Combined)

4..Hogg et al. (1986)

5..Negri et al. (1984)

6..Lovejoy and Austin (1979)

Figure 5. PLOT OF VALIDATION ERRORS FOR DIFFERENT TECHNIQUES (Sample 2)



Technique 1..IR & Vis.

2..Radar (unadjusted)

3..IR, Vis. & Radar (Combined)

4..Nogg et al. (1986)

5..Negri et al. (1984)

6..Lovejoy and Austin (1979)

TABLE 1

Daily Gauge Data

No.	Day	Rainfall Gauge Observation (mm)
1	April 2, 1985	4.36
2	April 3, 1985	2.77
3	April 4, 1985	10.86
4	April 6, 1985	1.45
5	April 7, 1985	1.54
6	April 8, 1985	0.99
7	April 9, 1985	0.11
8	April 10, 1985	2.24
9	April 11, 1985	0.25
10	April 12, 1985	0.32
11	April 13, 1985	1.76
12	April 14, 1985	0.87
13	April 15, 1985	0.13
14	April 16, 1985	0.29
15	April 17, 1985	2.58
16	April 18, 1985	5.35
17	April 19, 1985	3.05
18	April 20, 1985	0.13
19	April 21, 1985	0.49
20	April 22, 1985	0.20
21	April 23, 1985	0.22
22	April 24, 1985	2.86
23	April 25, 1985	0.25
24	April 26, 1985	0.73
25	April 27, 1985	1.08
26	April 28, 1985	0.69
27	April 29, 1985	0.00

TABLE 2
Summary of Results of Application of Prediction Equations

Sr. No.	Calibration Data (Days) April, 1985	Validation Data (Days) April, 1985	Dependent Variable	Independent Variable			Correlation Coefficient (R)	Standard Prediction Error of Validation (%)
			Precipitation (mm)	vis & IR Day	IR Night	Radar Unadjusted		
1	2-4, 6-29	-	x	-	x	-	0.83	-
2	2-4, 6-29	-	x	x	x	-	0.84	-
3	2-4, 6-29	-	x	-	-	x	0.92	-
4	2-4, 6-29	-	x	x	x	x	0.94	-
5	3, 4, 7, 8, 10-12, 14, 15, 17, 19, 20, 22-24, 26, 28	2, 6, 9, 13, 16, 18, 21, 25, 27, 29	x	-	x	-	0.80	53
6	"	"	x	x	x	-	0.81	52
7	"	"	x	-	-	x	0.96	83
8	"	"	x	x	x	x	0.97	74
9	2, 6, 7, 9, 10, 12, 13, 16-18, 21-23, 25-27, 29	3, 4, 8, 11, 14, 15, 19, 20, 24, 28	x	-	x	-	0.87	133
10	"	"	x	x	x	-	0.88	132
11	"	"	x	-	-	x	0.81	114
12	"	"	x	x	x	x	0.94	123

TABLE 3

Validation Results using Trivariate Regression Using Satellite vis & IR Data (Sample 1)

Sr. No.	Calibration Data (Days) April, 1985	Daily Average Precipitation (mm)		Prediction Error (mm)
		Estimated (from Regression)	Actual (Gauge Data)	
1	3, 4, 7, 8, 10-12, 14, 15, 17, 19, 20, 22-24, 26, 28	2.756	4.360	1.604
2	"	1.810	1.448	0.362
3	"	0.410	0.107	0.303
4	"	1.560	1.759	0.199
5	"	1.110	0.286	0.824
6	"	4.619	5.348	0.729
7	"	0.419	0.489	0.070
8	"	1.248	0.247	1.001
9	"	0.579	1.078	0.499
10	"	0.580	0	0.580

TABLE 4

Validation Results using Trivariate Regression Using Satellite VIS & IR Data (Sample 2)

Sr. No.	Calibration Data (Days) April, 1985	Daily Average Precipitation (mm)		Prediction Error (mm)
		Estimated (from Regression)	Actual (Gauge Data)	
1	2, 6, 7, 9, 10, 12, 13, 16-18, 21-23, 25-27, 29	3.236	2.773	0.463
2	"	10.480	10.858	0.378
3	"	1.410	3.050	1.640
4	"	0.253	0.994	0.741
5	"	0.196	0.252	0.056
6	"	1.119	0.872	0.247
7	"	1.129	0.134	0.995
8	"	5.370	0.132	5.238
9	"	0.943	2.856	1.913
10	"	0.469	0.688	0.219

TABLE 5

Validation Results using Bivariate Regression Using Unadjusted Radar Data (Sample 1)

Sr. No.	Calibration Data (Days) April, 1985	Daily Average Precipitation (mm)		Prediction Error (mm)
		Estimated (from Regression)	Actual (Gauge Data)	
1	3, 4, 7, 8, 10-12, 14, 15, 17, 19, 20, 22-24, 26, 28	1.425	4.360	2.935
2	"	0.560	1.448	0.888
3	"	0.790	0.107	0.683
4	"	0.927	1.759	0.832
5	"	0.609	0.286	0.323
6	"	3.580	5.348	1.768
7	"	0.754	0.489	0.265
8	"	0.570	0.247	0.323
9	"	1.280	1.078	0.202
10	"	0.500	0	0.500

TABLE 6

Validation Results using Bivariate Regression Using Unadjusted Radar Data (Sample 2)

Sr. No.	Calibration Data (Days) April, 1985	Daily Average Precipitation (mm)		Prediction Error (mm)
		Estimated (from Regression)	Actual (Gauge Data)	
1	2, 6, 7, 9, 10, 12, 13, 16-18, 21-23, 25-27, 29	0.924	2.773	1.849
2	"	15.312	10.858	4.454
3	"	4.103	3.050	1.053
4	"	2.120	0.994	1.126
5	"	0.507	0.252	0.255
6	"	1.288	0.872	0.416
7	"	0.609	0.134	0.475
8	"	0.610	0.132	0.478
9	"	3.378	2.856	0.522
10	"	0.559	0.688	0.129

TABLE 7

Validation Results using Multivariate Regression Using Satellite & Unadjusted Radar Data (Sample 1)

Sr. No.	Calibration Data (Days) April, 1985	Daily Average Precipitation (mm)		Prediction Error (mm)
		Estimated (from Regression)	Actual (Gauge Data)	
1	3, 4, 7, 8, 10-12, 14, 15, 17, 19, 20, 22-24, 26, 28	1.600	4.360	2.760
2	"	0.858	1.448	0.590
3	"	0.645	0.107	0.538
4	"	1.025	1.759	0.734
5	"	0.609	0.286	0.323
6	"	3.900	5.348	1.448
7	"	0.615	0.489	0.126
8	"	0.610	0.247	0.363
9	"	1.108	1.078	0.030
10	"	0.417	0	0.417

TABLE 8

Validation Results using Multivariate Regression Using Satellite & Unadjusted Radar Data (Sample 2)

Sr. No.	Calibration Data (Days) April, 1985	Daily Average Precipitation (mm)		Prediction Error (mm)
		Estimated (from Regression)	Actual (Gauge Data)	
1	2, 6, 7, 9, 10, 12, 13, 16-18, 21-23, 25-27, 29	2.300	2.773	0.473
2	"	15.060	10.858	4.202
3	"	3.160	3.050	0.110
4	"	0.980	0.994	0.014
5	"	0.032	0.252	0.220
6	"	1.110	0.872	0.238
7	"	0.740	0.134	0.606
8	"	3.590	0.132	3.458
9	"	2.130	2.856	0.726
10	"	0.270	0.688	0.418